Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 81 (2019) 1337–1341

www.elsevier.com/locate/procedia

52nd CIRP Conference on Manufacturing Systems

The effect of operational policies on production systems robustness: an aerospace case study

Emanuele Pagone[a], Konstantinos Efthymiou[b], Brandon Mahoney[b], Konstantinos Salonitis[a]*

[a]*Sustainable Manufacturing Systems Centre, School of Aerospace, Transport and Manufacturing, Cranfield University, Bedford, UK*
[b]*Applied Research & Technology, Meggitt PLC, Coventry, UK*

* Corresponding author. *E-mail address:* k.salonitis@cranfield.ac.uk

Abstract

This study aims to evaluate the robustness of a low volume mixed model production line under different operating conditions. A real production line that builds six different aircraft heat exchangers is modelled, simulated and analysed under different operating conditions. A number of experiments are conducted in order to assess the effect of dispatching rules and disturbances related to reworks, and processing time variance on tardiness robustness. A penalty function to quantitatively assess tardiness is defined based on lead time at capacity and it is used to measure the robustness of the system. The results of the assessment are then discussed in order to give some practical guidance to production planners with controlling the line in the face of uncertainty or disturbances similar to those evaluated in the study.

Keywords: robustness, aerospace, digital manufacturing, production systems planning & control.

1. Introduction

Uncertainty affects significantly manufacturing systems both within the boundaries of the plant and externally [1,2]. It is critical for the competitiveness of such enterprises to be able to cope with expected and unexpected disturbances to achieve the set targets in a reliable fashion. Most modern planning approaches aim at optimising Key Performance Indicators (KPIs) like lead time and WIP although it is also of paramount importance to exhibit robustness and resilience in the face of disturbances.

Neglecting the importance of robustness can force planners to deal with potential disruptions by increasing the redundancy of resources or increasing the time windows in their productions plans. All such approaches may easily cancel any benefit of lead time optimisations, for example.

Research efforts towards the definition of robustness can be identified both in the domains of academia and industry. Academic works are focused on theoretical models based on complex mathematical formulations or on more practical approaches intended to provide planners with supporting tools for their daily tasks. For example, Colledani *et al.* suggest a distinction between proactive (with redundancy and overcapacity) and reactive (acquiring the ability to react quickly) robustness in the design stage in the automotive industry [3]. Such concept is included in a framework for the design and management of modular, reconfigurable assembly systems described by a relatively high level of abstraction [3]. Tolio *et al.* define Value at Risk (VaR) as a robustness metric to assess tardiness. VaR is defined on probabilistic terms to develop a scheduling algorithm that controls a CNC machine [4] or an isolated machine using a "branch and bound" strategy [5]. Telmoudi *et al.* distinguish active and passive robustness considering if the system has to modify its control parameters or not to preserve its specified properties against disturbances [6]. Stricker and Lanza provide a number of definitions of robustness before suggesting a general definition as the stability of the system against different varying conditions [7]. Furthermore, the authors compare robustness with closely related concepts like flexibility, resilience and risk [7]. More

10.1016/j.procir.2019.04.023

practical approaches to increase robustness in manufacturing systems suggest the implementation of redundancies and the increase of reserved capacity [8,9]. These works by Meyer *et al*. focus mainly on internal disturbances and define robustness as the ratio between a performance indicator in a system with disturbances and one undisturbed [8,9]. As previously observed, although such practical approach is more useful for the daily tasks of planners, the suggested measures to increase robustness are likely to increase costs.

The industrial approach to robustness can be connected to the efforts to minimise variation and waste of resources in non-adding value activities, i.e. 6-sigma and lean philosophy [10]. Sectorial information technology tools like Enterprise Resource Planning (ERP) and Manufacturing Execution Systems (MES) are in principle well suited to manage robustness from the point of view of planners. However, in practice, very little and limited attention is devoted to the inclusion of disruptive events or uncertainty while planning at strategic level [10]. Robustness and modelling of stochastic systems are generally not assessed or controlled in ERP and MES frameworks [10]. Planning adaptation to cope with disturbances is usually implemented in the short-term time frame with frequent actions and no strategic vision, relying on the experience of planners rather than on tools or systematic methods [10]. Furthermore, besides the opportunity to include robustness and stochastic modeling in traditional ERP and MES, it is also possible to consider for their implementation the emerging trend of technologies included under the umbrella of Industry 4.0 [11]. Decentralised, multi-agent based scheduling systems deriving from these technologies may actually provide a more advanced and fine-tuned approach to robustness in manufacturing firms [12]. However, as always happens with emerging opportunities, industrial deployment can be started only when a minimum degree of maturity has been proven beyond demonstrative pilot lab examples [13].

This work builds on a previous study [10] where a robustness indicator is defined and it is included in a methodology aimed at production planners. The advantage of the proposed metric is twofold. On the one end, it is a practical indicator that represents the entire, complex manufacturing system with its stochastic nature, without resorting to abstract simplifications like in the operations research literature. On the other hand, it can summarise such complex system with a single value that promotes its pragmatic adoption by production planners. This paper uses the mentioned framework to present a systematic analysis evaluating the robustness of tardiness in 18 scenarios of a real manufacturing line in the aerospace sector. To this aim, a tardiness penalty function is proposed assessing its robustness against disturbances during assembly and rework of mixed model products.

The proposed robustness metric and relevant framework is briefly presented in Section 2 whereas Section 3 provides the reader with a description of the industrial case study chosen to illustrate the application of the framework. The results are presented and discussed in Section 4 before a final conclusion summarising the findings and discussing the potential direction of future work.

2. Manufacturing systems robustness evaluation

This section describes initially the quantitative metric chosen to describe robustness and then the methodology used to perform the analysis.

2.1. Definition of robustness

A manufacturing system that can preserve its performance stability, without any significant deviation from the planned goals against foreseen or unforeseen disturbances, can be considered as robust. The performance of a manufacturing system is assessed with KPIs. Hence, in this paper robustness of a manufacturing system is connected with the robustness of KPIs. In particular, the higher the probability of the system to meet KPI goals in the face of disturbances for different operating conditions, the higher the robustness. This approach has the advantage to provide a quantitative measure that can be formalised mathematically considering a function f that describes the manufacturing system, associating an input set of operating conditions or scenarios S to a number of (output) KPIs (real variables) [10]:

$$f(S) \rightarrow \boldsymbol{R} \tag{1}$$

As previously described, if the aim is to measure the probability of the system to meet targets linked to KPIs, the stochastic nature of the operating conditions S should be captured, i.e. S is a random variable. Thus, also the output of f (i.e. the values of KPIs) is stochastic in the set of real numbers. Furthermore, a certain threshold value for a KPI, or acceptable limit $L \in \mathbf{R}$ can be defined so that $f(S) \leq L$ is desired (assuming $f(S)$ is some sort of "cost" function to be minimised, although the derivations can be easily developed in the case of a "benefit" function to be maximised). Hence, the robustness function of the system F calculated at the limit L is defined on probabilistic terms:

$$F(L) = Pr(f(S) \leq L) \tag{2}$$

2.2. Robustness assessment

Four main steps have been devised to appraise the robustness of the manufacturing system:

1. System definition,
2. Operating conditions set,
3. Simulation building and run,
4. Statistical post-processing of results.

In a first phase, the system basic specifications are defined. The types and routing of products, the capacity of buffers, a list of the resources available with their processing and set-up times is essential information to be collected at this stage. To represent significantly the behaviour of the system in real life, stochasticity is considered for processing and set-up times. This is important not only to describe the intrinsic variation during normal operations, but also to accommodate the characteristic uncertainty of any data collection method.

Subsequently, additional conditions are applied to define the scenarios to be considered. Information collected or defined at this stage includes: demand profile and its dispatching rules, batch sizing and its transport, control policies, the KPIs and the disturbances with their relevant limits. It is possible to consider at this stage both internal source of disturbances (e.g. machine breakdowns, lack of personnel, scrap and rework occurrence, variation of process times) and external ones (e.g. supplier delays and demand uncertainty). This work will focus on internal disturbances.

The implementation and execution of the simulations describing the chosen scenarios can be performed with a number of tools. In this paper Discrete Event Simulations (DES) are chosen for their aptitude to describe complex manufacturing systems and their associated stochastic nature. Furthermore, although a relatively large quantity of data is necessary to generate a representative DES model, other approaches like stochastic queueing theory [14], do require a higher level of abstraction that is not suitable for the case at hand. Each scenario is executed a number of times to record the stochastic variability of KPIs with an adequate confidence level.

The final statistical analysis of results allows the quantification of robustness at the limit L for the selected KPIs. To this aim, a normal distribution is considered according to the central limit theorem. The above procedure should be applied with care in case of significantly rare or common events. In particular, tailored sampling techniques to deal with such cases should be adopted.

3. Industrial Case Study

3.1. Products

Six different types of product are considered in this study. They are all tubular matrices of aircraft engines heat exchangers.

3.2. Production Line

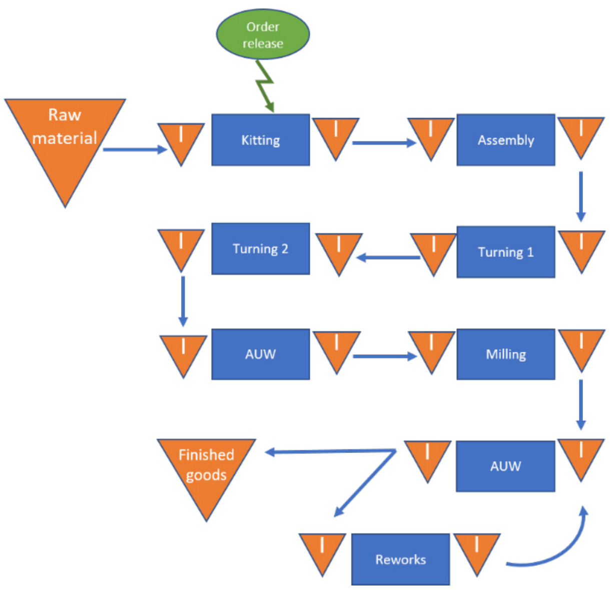

Fig. 1. Production line steps.

A common product routing is analysed in this work (Fig. 1). When an order is released, kits of the relevant product type are collected and assembled in batches by two kitters and ten assemblers. Then, machining is performed in three serial steps: turning with lathe one (Turning 1) and lathe two (Turning 2) and, finally, milling. Four machinists with different skills, work in this area. A final inspection to check leakages is performed at an Air-Under-Water (AUW) station that determines if the product must be reworked. Tests and repairs will be repeated until the part successfully passes the AUW inspection.

3.3. Production Planning & Performance Indicators

Starting from a reference demand profile, three dispatching rules have been tested: First In First Out (FIFO), Shortest Processing Time (SPT) and Earliest Due Date (EDD). FIFO is considered the baseline whereas both SPT and EDD re-sort the orders on a weekly basis according to their rules. SPT prioritises part types with the shortest expected processing time while EDD is based on the due date estimated multiplying the same expected processing time by its standard deviation. The mentioned expected time is measured as a weekly running average with the system working at capacity.

The performance indicator considered to assess robustness is tardiness, evaluated as a function of lead time, that is the time elapsed between the release of the order and the completion of the finished part. A penalty function π is defined as follows:

$$\pi = \sum_i \frac{\Delta t_{dd,i}}{t_{dd,i}} \tag{3}$$

where Δt_{dd} is the positive time difference between the actual lead time of the i-th part and the time at the due date t_{dd}.

Three types of disturbances are considered: the variance of assembly and rework time and the probability of rework occurrence. Both activities are carried out by human operators and, therefore, are stochastic in nature. However, for the assembly times, a fixed reference value is considered while the rework times are described by a statistical triangular distribution of probability. The rework occurrence is defined on probabilistic terms too.

3.4. Operational Policies & Disturbances Scenarios

A total of 18 scenarios are investigated according to a “design of experiment” approach where one independent variable at the time is changed in comparison to the baseline case. The mentioned independent variables are the dispatching rules (FIFO, SPT and EDD) and the disturbances (assembly and rework time variance and probability of rework). The dependent variable of the experiments is the robustness of the performance indicators, i.e. average tardiness function and lead time.

The variability of the disturbances has been handled defining specific, multiplicative factors hereafter detailed. In the case of assembly time, the chosen reference value is constant for each part type and it is used as the mode of a symmetric triangular probability distribution constructed using an assembly time factor f_{at}. The bounds of the distribution are set multiplying the mode by f_{at} and $1 - f_{at}$ accordingly. The rework time for the baseline is defined with a triangular probability distribution with coefficient of variation $c_v = \sigma/\mu$ (with σ standard deviation and μ mean). This value is scaled by factor f_{rt}, obtaining the coefficient of variation of the new triangular distribution c'_v:

$$c'_v = c_v\, f_{rt} \tag{4}$$

Imposing that the mode c and mean μ do not change, Eq. (4) yields: $\sigma' = \sigma\, f_{rt}$. Hence, the three unknowns describing the new probability distribution (i.e. the bounds a', b' and the mode c') are obtained solving the following system of equations using 1) the previously set condition that the mode do not change, 2) the equality of the mean for both distributions, 3) scaling the standard deviation by f_{rt}. Substituting the expression of the mean and standard deviation as a function of the bounds (a and b) and mode c, the following system of equation is obtained

$$\begin{cases} c' = c \\ \frac{a'+b'+c'}{3} = \frac{a+b+c}{3} \\ \sqrt{\frac{a'^2+b'^2+c'^2-a'b'-a'c'-b'c'}{18}} = \sqrt{\frac{a^2+b^2+c^2-ab-ac-bc}{18}}\, f_{rt} \end{cases} \tag{5}$$

Considering that the first equation is trivial and is decoupled, the problem reduces to a system of two equations in two unknowns. Finally, the probability of a rework to occur is controlled by the multiplicative factor f_{ro}.

Basic sanity checks are implemented in the model to ensure that the resulting time distributions do not reduce below an unrealistic threshold and that the final probability of reworks is always bounded between 0 and 1.

The specific values introduced for the above parameters in each of the 18 simulated scenarios are summarized in Tab. 1.

The DES model is built and simulations performed with Siemens Tecnomatix Plant Simulation [15] that was interfaced to a numerical solver written in Modern Fortran using a modification of the Powell hybrid method [16] to resolve Eqs. (5). Simulations are performed for one year of production where satisfactory steady-state conditions are observed.

Table 1. Scenarios and independent variables.

Scenarios	Dispatching rules	Assembl time (f_{at})	Rework time (f_{rt})	Rework occur (f_{ro})
A, B, C	FIFO, SPT, EDD	1	1	1
D, E, F	FIFO, SPT, EDD	1.2	1	1
G, H, I	FIFO, SPT, EDD	1	1.1	1
J, K, L	FIFO, SPT, EDD	1	1	1.2
M, N, O	FIFO, SPT, EDD	1	0.9	1
P, Q, R	FIFO, SPT, EDD	1	1	0.8

4. Results & Discussion

The histogram plot of the tardiness penalty function π for a sample case, confirms the correctness of the normal distribution assumption when a sufficiently large number of replications (in this case 20) of the same case are executed (Fig. 2). Furthermore, on the chart it is visible (represented by the red, dashed line) the threshold limit value L used to determine the robustness F. This quantity is approximated by the area of the histogram to the left of L according to the definition in Section 2.1 and Eq. (2) and, thus, higher values represent a more robust system.

Comparing the robustness of tardiness in the different scenarios (Fig. 3), it is possible to identify the impact and extent of the selected independent variables (see Tab. 1).

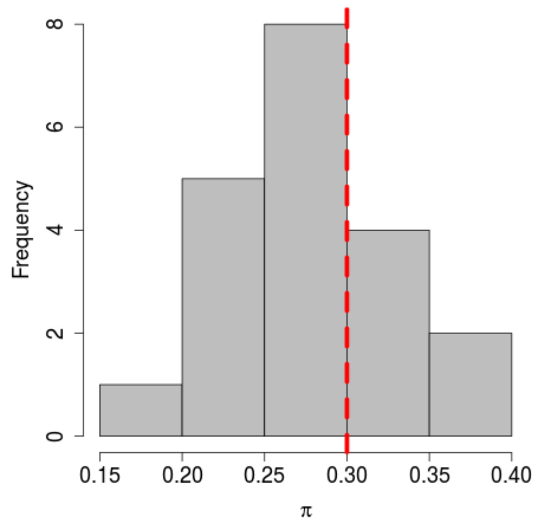

Fig. 2. Sample distribution of the observed tardiness penalty function π for one scenario over repeated runs. The red, dashed line shows the limit considered to assess the robustness.

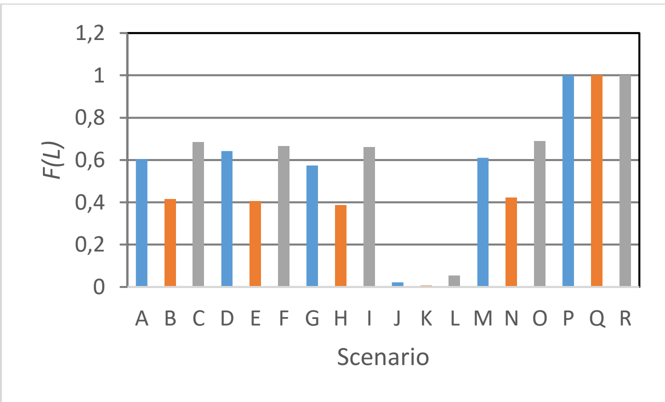

Fig. 3. Robustness F of the tardiness penalty function at limit L for the 18 scenarios defined in Tab. 1. The colour of the bars indentify the dispatching rule. Blue: FIFO, orange: SPT, grey: EDD.

Between the dispatching rules, EDD shows (as intuitively predictable) an improvement in comparison with FIFO (scenarios C, F, I, L and O versus A, D, G, J and M). However, it is interesting to notice that SPT does not improve the baseline tardiness robustness. A potential explanation of such finding could be the inaptitude of SPT to organise the dynamic demand over the year.

Furthermore, assembly time variability does not appear to affect robustness in a significant way (scenarios A, B, C versus D, E, F), although a modest, expected reduction is visible. The same comment can be made in the regards of rework time: its variability does not strongly affect tardiness regardless of its increase (scenarios G, H, I) or reduction (scenarios M, N, O).

Finally, it can be concluded that changing the probability of a rework to occur has a significant impact of the robustness of tardiness (scenarios J, K, L and P, Q, R). In particular, when the relevant probability is reduced by 20% (scenarios P, Q, R) the prospect to miss the set deadline never holds, statistically.

5. Conclusion & Future Work

In this work, a framework and relevant metric to assess robustness in manufacturing systems are presented. Such tool combines the data collection of key aspects of the system (like routings, performance indicators and disturbances) with stochastic simulations and statistical analyses. The application of the framework is illustrated applying it to a low volume, mixed model production line of an aerospace manufacturer. A suitable tardiness function (based on lead time and expected due date) is introduced alongside three disturbances: the time variability in the assembly and rework process and the probability for a part to fail a quality test and then be repaired. Furthermore, three different dispatching rules (First In First Out, Shortest Processing Time and Earliest Due Date) are investigated. The results show that the proposed definition of robustness can be applied effectively to tardiness and identify the impact of different disturbances in a quantitative manner. Future work will be aimed at a more extensive application of the proposed framework to describe more accurately the manufacturing system and propose further changes to improve the performance.

Acknowledgements

This work has been supported by the research project “Meggitt Modular Modifiable Manufacturing” (M4) M4 15-002 funded by the ATI & Innovate UK. The authors would also like to acknowledge the support from Cranfield University MSc student Raphael S. Halitim.

References

[1] Chryssolouris G. Manufacturing Systems: Theory and Practice. Springer, New York; 1992.

[2] Efthymiou K, Mourtzis D, Pagoropoulos A, Papakostas N, Chryssolouris G. Manufacturing systems complexity analysis methods review. Int. J. Comput. Integr. Manuf. 2016; 29(9).

[3] Colledani M, Gyulai D, Monostori L, Urgo M, Unglert J, Van Houten F. Design and management of reconfigurable assembly lines in the automotive industry. CIRP Annals 2016; 65(1) p. 441-446.

[4] Tolio T, Urgo M, Vancza J. Robust prediction control against propagation of disruptions. CIRP Annals 2011;

[5] Urgo M, Vancza J. A robust scheduling approach for a single machine to optimize a risk measure. Procedia CIRP 2014.

[6] Telmoudi AJ, Nabli L, M’hiri R. Robust control of a manufacturing system: Flow-quality approach. IEEE Int. Conf. Emerg. Technol. Fact. Autom. EFTA 2017;

[7] Stricker N and Lanza G. The concept of robustness in production systems and its correlation to disturbances. Procedia CIRP 2014.

[8] Meyer M, Apostu MV, Windt K. Analysing the influence of capacity adjustments on performance robustness in dynamic job-shop environments. Procedia CIRP 2013.

[9] Meyer M. Redundancy investments in manufacturing systems: the role of redundancies for manufacturing systems robustness. 2016.

[10] Efthymiou K, Shelbourne B, Greenhough M, Turner C. Evaluating manufacturing systems robustness: an aerospace case study. Procedia CIRP 2018; 72 p. 653-658.

[11] Jackson K, Efthymiou K, Borton J. Digital manufacturing and flexible assembly technologies for reconfigurable aerospace production systems. Procedia CIRP 2016; 52 p. 274-279.

[12] Colombo AW. Industrial cloud-based cyber-physical systems: the IMC-AESOP approach.

[13] Leitao P, Colombo AW, Karnouskos S. Industrial automation based on cyber-physical systems technologies: prototype implementations and challenges. Comp. Ind 2016; 81 p. 11-25.

[14] Rooda JE, Vervoot J. Analysis of Manufacturing systems. Technische Universiteit Eindhoven, Department of Mechanical Engineering; 2005.

[15] Tecnomatix Plant Simulation: Siemens PLM Software. [Online]. Available: https://www.plm.automation.siemens.com/store/en-us/plant-simulation. [Accessed: 19-Feb-2019].

[16] More JJ, Garbow BS, Hillstrom KE. User guide for MINPACK-1. Argonne National Laboratory Report ANL-80-74. Argonne. 1980.

Van der Geer J, Hanraads JAJ, Lupton RA. The art of writing a scientific article. J Sci Commun 2000;163:51-9.

[17] Strunk Jr W, White EB. The elements of style. 3rd ed. New York: Macmillan; 1979.

2019-06-24

The effect of operational policies on production systems robustness: an aerospace case study

Pagone, Emanuele

Elsevier

Pagone E, Efthymiou K, Mahoney B, Salonitis K. The effect of operational policies on production systems robustness: an aerospace case study. Procedia CIRP, Volume 81, 2019, Pages 1337-1341
https://doi.org/10.1016/j.procir.2019.04.023